A CASE STUDY OF SOCIAL VULNERABILITY MAPPING:

ISSUES OF SCALE AND AGGREGATION

A Thesis

by

GABRIEL RYAN BURNS

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2007

Major Subject: Geography

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Approved by:

Chair of Committee,	Robert Bednarz
Committee Members,	Andrew Klein
	Carla Prater
Head of Department,	Douglas Sherman

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ABSTRACT

A Case Study of Social Vulnerability Mapping: Issues of Scale and Aggregation.

(May 2007)

Gabriel Ryan Burns,. B.S. Texas A&M University

Chair of Advisory Committee: Dr. Robert Bednarz

This study uses geographic information systems to determine if the aggregation of census block data are better than census block group data for analyzing social vulnerability. This was done by applying a social vulnerability method that used census block group data for a countywide analysis and converting it to use census blocks for a countywide analysis and a municipal-wide analysis to determine which level of aggregation provided a more precise representation of social vulnerability. In addition to calculating the social vulnerability, the results were overlaid with an evacuation zone for the threat of a train derailment, determining which aggregation better depicted at-risk populations.

The results of the study showed that the census blocks enable a more exact measurement of social vulnerability because they are better at capturing small pockets of high-risk areas. This study concludes that census block are more advantageous than census block groups because they are more sensitive and geographically exact in measuring social vulnerability, allow for a better interpretation of social vulnerability for smaller areas, and show spatial patterns of vulnerability at a finer spatial scale.

DEDICATION

To my family

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I would like to thank my advising chair Dr. Robert Bednarz for his guidance and patience on my research and graduate career as well as other miscellaneous advice I inadvertently received through our conversations. I also want to thank my other committee members Dr. Carla Prater and Dr. Andrew Klein for being very sincere and providing valuable feedback on my research. I would also like to thank Dr. Sarah Bednarz for giving me the opportunity to work with a wonderful group of educators and their students. Thanks to all of you for helping me become a better geographer and scientist.

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CHAPTER I

INTRODUCTION: VULNERABILITY AS A CHALLENGE TO GEOGRAPHY

Calculating and mapping a population's vulnerability to environmental hazards is a challenge in geography. The difficulty is how to differentiate locations and social characteristics that create concentrations of vulnerability. Population growth has expanded human occupation into spaces previously uninhabitable and prone to hazards from natural phenomena to anthropogenic calamities (Burton, Kates, and White 1993). The effects of these environmental hazards can change where and how a population develops (Van der Veen and Logtmeijer 2005). A challenge for geographers is locating vulnerable populations, and calculating what makes these populations susceptible to harm from environmental hazards before a calamity happens. This study examines the challenges of mapping and calculating social vulnerability by expanding on concepts and knowledge of scale and aggregation.

Hazard Nomenclature

Research in environmental hazards is transdisciplinary, meaning that terminology and definitions vary with different research disciplines. This study uses terminology defined in fields related to geography. Environmental hazards are extreme events that depart from a geophysical or anthropogenic trend (Alexander 2000). They are hazardous

This thesis follows the style and format of *Annals of the American Association of Geographers*.

when they come into human contact and causing, in most cases, recurring damage or harm to a population (Alexander 2000; Burton, Kates, and White 1993; Hewitt and Burton 1971; Smith 2001). Destruction from environmental hazards results from population growth, urban expansion and human attempts to conquer extreme environments. Environmental hazards can be confused with the term disaster. Environmental hazards are events or agents with the potential for occurrence. Disasters are the actual occurrence and aftermath.

Environmental hazard events are divided into three categories: natural, technological, and willful (Alexander 2000; Smith 2001). A natural hazard describes an extreme geophysical event that is natural in origin and occurs singly or in combination with other environmental factors (Alexander 2000). Research on natural hazards includes works on such events as hurricanes (Peacock 2003), volcanoes (Parechi et al. 2000), and earthquakes (Kates et al. 1973). A technological hazard is a sequence of human technological processes, which causes a release of material and/or energy onto a population causing harmful exposure (Hohenemser, Kates, and Slovic 1983). Research on these hazards focus on chemical spills, toxic releases (Cutter, Scott, and Hill 2002; Thomas, Qin, and Richardson 2001), nuclear power plant accidents (Lindell and Perry 1990) and transportation-related accidents. The final form of hazard is willful. Willful hazards include acts of terrorism, warfare, and other purposely harmful anthropogenic actives inflicted on a population (Peek and Sutton 2003; Perry and Lindell 2003).

Depending on their severity these three hazard categories frequently trigger additional hazards known as secondary hazards (Wisner et al. 2004). An example of a secondary hazard is a chemical spill caused by an earthquake. Because of the varying degree of interlinking qualities in the hazard categories, it is easier to categorize them under the umbrella of environmental hazards. Environmental hazards therefore encompass all types of hazards. This is important for researchers who study the disastrous effects and damages from environmental hazards and help develop strategies to reduce their impacts. It is also important to remember that these strategies only reduce, not eliminate, damages. Environmental hazards always cause a certain degree of damage to people, plants or animals. Hazard research is vital to prevent widespread damage to unprepared areas.

One avenue of hazard research looks at population vulnerability. Vulnerability is a multi-faceted term incorporating susceptibility and impact to determine the potential for loss from a hazard event (Cutter 2001; Cutter, Boruff, and Shirley 2003; Wisner et al. 2004). The concept of vulnerability does not assume a uniform distribution spatially or demographically for loss or coping capacity (Hill and Cutter 2001).

There are three categories of vulnerability: individual, biophysical and social, which define the threat of exposure of an area, the capacity for damage, and the degree of suffering for different social groups (Cutter 1996, 2001). Individual vulnerability refers to the susceptibility of a person to potential harm from a hazard, including exposure to conditions, which could cause death, injury or illness (Hill and Cutter 2001). Biophysical vulnerability refers to physical exposure to and proximity of hazardous conditions such as magnitude, duration, frequency, and impact from environmental hazards (Hill and Cutter 2001). Lastly, what this study focuses on is social vulnerability.

Social vulnerability describes demographic characteristics of social groups that make them more or less susceptible to the adverse impacts of environmental hazards (Cutter 1996; Cutter, Boruff, and Shirley 2003; Cutter, Mitchell, and Scott 2000; Hill and Cutter 2001). Furthermore, social vulnerability suggests the potential for loss and ability to recover from environmental hazard events are functions of a range of social, economic, historic, and political processes (Hill and Cutter 2001; Wisner et al. 2004).

Terminology and definition of environmental hazards and vulnerability are important for the municipal, state, and federal agencies, who are responsible for protecting and sustaining their citizen's wellbeing. Hazard terminology was important for the conceptualization of the disaster cycle. The disaster cycle is a conceptual model characterized by four temporal stages: mitigation, preparation, response, and recovery (Alexander 2002; Perry and Lindell 2003; Tierney, Lindell, and Perry 2001). The model is based on a 1978 meeting of the National Governors Association (NGA). During the meeting, the NGA outlined a plan to coordinate various government entities to establish a comprehensive emergency management to ensure a set of emergency protocols pre and post hazard event. Figure 1 is a revised version of the original NGA model with an alternative and overlapping set of actions. Though many variations of this model exist, the concept and definitions remain the same. The model defines mitigation as preliminary actions taken before a disaster such as enactment of city zoning regulations and structure design codes. Preparedness includes actions taken before an environmental hazard event such as organizational planning by citizen advisory committees and community evacuation plans. Response is the period of immediate action before, during and after the impact of an environmental hazard. Recovery is the process of restoring the community from the social and economic disruptions created by an environmental hazard. However, the manner in which the public will follow emergency plans and the unpredictable nature of environmental hazards can create planning problems when trying to follow the disaster cycle. This model is not meant as a simple sequential series of steps, but rather as a set of functions that must be carried out.

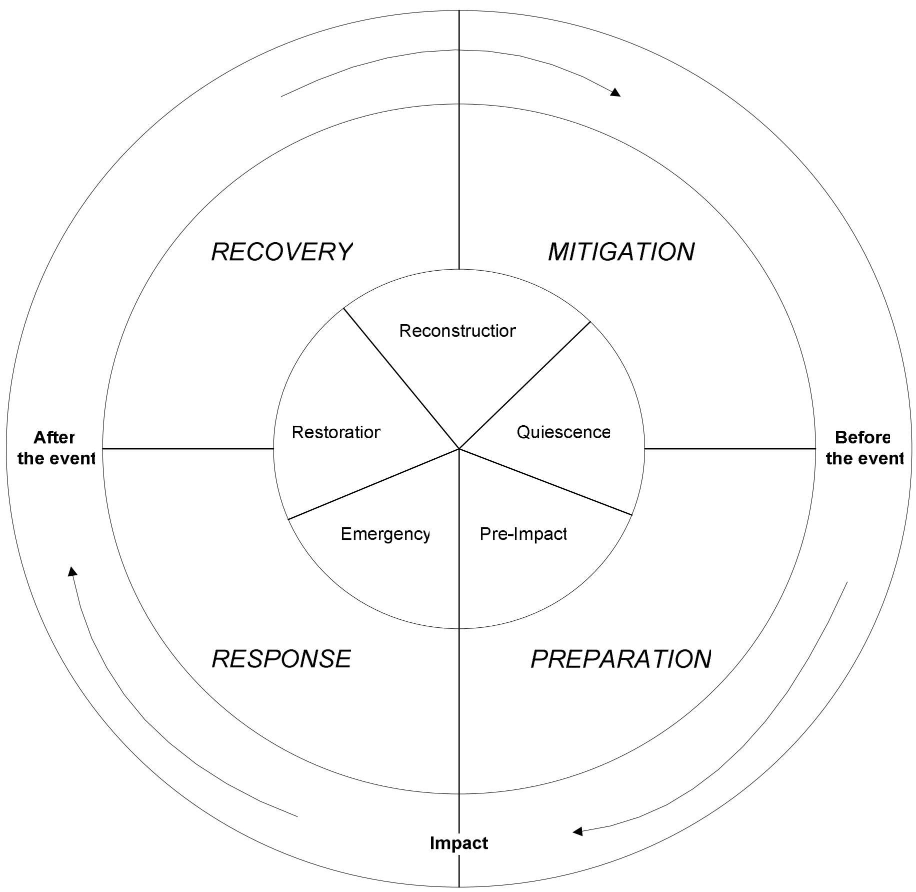

Figure 1: Disaster Cycle. (Modified from Alexander 2002)

Research Problem

One concern emergency managers and policy administers face is determining a population's vulnerability to hazards. Geographic research indicates that some social groups live in highly vulnerable areas either out of necessity, default, or desire (Alexander 2000). By calculating the vulnerability of social groups, emergency managers and political officials can more effectively respond to the adverse impacts of hazards (Cutter, Mitchell, and Scott 2000). Research in calculating and mapping social vulnerability has gained more interest since the 2005 Hurricane Katrina disaster. Though the areas affected by the hurricane had social vulnerability related research, there was little to no mapping of the areas, which could have helped identify the location of those social groups in greater need of evacuation. However, there are problems in the current methods of social vulnerability calculation and mapping. Current methods often use too large of aggregated areas that may distort social vulnerability calculations. This distortion, projected onto maps, may display socially vulnerable areas too broadly, creating a homogenous view of vulnerability when in fact the large areas mask meaningful geographic variation (Bednarz and Tenfjord 1997; Tenfjord 1998). Therefore, it is imperative for emergency managers to calculate and map social vulnerability at an appropriately aggregated spatial scale, which provides a more exact understanding of vulnerability for a region.

In geography, the most influential method for calculating and mapping social vulnerability was developed by Cutter, Mitchell, and Scott (1997). They based their assessment method on Federal Emergency Management Agency (FEMA) standards for county-level hazard identification and used demographic information at the census block group (CBG) level to calculate social vulnerability. Their examination provided a model for assessing a county's hazard and social vulnerability characteristics. In that study, hazard vulnerability was defined as the frequency of hazards occurring within a county. Social vulnerability was based on the demographic characteristics of the county's population sub-groups. These characteristics made social sub-groups more or less susceptible to the adverse impacts of hazards (Cutter, Boruff, and Shirley 2003). The Cutter, Mitchell, and Scott (1997) vulnerability analysis was designed to assist county government entities such as Councils of Governments (COGs). The study did not analyze municipal regions within the counties, however. This omission could affect the utility of the analysis especially for city governments. Furthermore, by failing to identify municipalities, the study excluded cities that overlap into adjacent counties limiting the applicability of vulnerability results for city governments and their residents.

The Cutter, Mitchell, and Scott (1997) social vulnerability method could be easily applied to municipalities. However, the use of CBG, which may combine areas both inside and outside the city, is not appropriate. The coarseness of CBG used in the Cutter, Mitchell, and Scott (1997) method may inaccurately depict the pattern of social vulnerability to municipal government decision makers. Calculating social vulnerability at the census block (CBLK) as opposed to CBG level may eliminate this problem and provide a more accurate analysis. Therefore, the central question of this study asks: Is the use of census block data advantageous when analyzing social vulnerability at the city level?

Research Objectives

To answer the research question, this study's research results will show that the using CBLK provides a more exact measurement of social vulnerability than CBG. First, countywide social vulnerability analysis is more exact if using CBLK than CBG. Second, municipal-wide social vulnerability analysis is more exact if using CBLK than CBG. Lastly, using CBLK social vulnerability results against the threat a potential hazard provides is more specific than CBG. This increase in accuracy could in turn aid municipalities within a county, who have more responsibility and therefore more pressing need to identify social vulnerability at a smaller spatial scale for emergency planning and government decision making. Additionally, growth in the application of geographic information to disaster research has created concerns that data is being used simply to show *what* happened in an emergency situation rather than supporting more in-depth analysis of *why* it happened, or what could have been done to avoid future problems (Tierney, Lindell, and Perry 2001).

Current strategies for determining social vulnerability have included various forms of technological advances to map hazards. These mapping procedures utilize geographic information technology based on Geographic Information Science (GIScience) to delineate vulnerable areas. GIScience is an approach that uses geographic information technologies such as geographic information systems (GIS), remote sensing (RS), and Global Positioning Systems (GPS) to collect and analyze spatial data in an automated and interpretive manner in order to address fundamental geographic issues (Cutter 2003; Goodchild 2003; Longley et al. 2005). GIS is an automated mapping program that combines spatial information with tabular attributes allowing the analytical capabilities to generate responses to geographic-based queries. These responses can enhance the computational and modeling capability for emergency response, preparation, hazard mitigation, and recovery in a geospatial context (Tierney, Lindell, and Perry 2001).

Research concerning hazard assessments has demonstrated that geographic information technology is a necessary tool in hazard-related projects. Dash (2002) has argued that geographic information technology can link physical elements of risk with the social, economic, and political elements that render certain areas vulnerable. These geographic technologies enable scientists and emergency managers to enhance their computational and modeling capability and allow them to manipulate large datasets to anticipate disaster-related problems (Tierney, Lindell, and Perry 2001).

Research Structure

To examine issues of vulnerability in geography, Chapter II discusses the hazards paradigm and the evolution of research in vulnerability as a social issue in geography. Chapter III presents an in-depth analysis of the methodology of the Cutter, Mitchell, and Scott (1997) social vulnerability assessment. The results of mapping Brazos County and the city of College Station's CBG and CBLK social vulnerability will be shown in Chapter IV. The final chapter will discuss the results to determine if they support the hypothesis. Issues of vulnerability and the use of geographic information technology as a significant tool for government decision making will also be discussed.

CHAPTER II

LITERATURE REVIEW: HAZARDS PARADIGM IN GEOGRAPHY

The study of environmental hazards is an established subfield in the discipline of geography. The hazards paradigm analyzes natural, technological, and willful hazards, collectively known as environmental hazards (Alexander 2000; Smith 2001). Geographical analysis in hazards is based on location and proximity, meaning that place and spatial attributes define the type and extent of an environmental hazard (Cutter 2001; Hewitt and Burton 1971). Since its emergence as a geography sub-discipline, hazards research has increased global awareness of concepts related to risk and vulnerability. Therefore, it is important to define geography's role in the study of hazards. As part of the introduction to the hazards paradigm, this section outlines the origins, critiques, and the modern movement and state of environmental hazard research, concluding with the direction that this thesis develops in the hazard paradigm.

Origins of Hazard Research

The origin of hazard research in geography began in 1922 with an address to the Association of American Geographers by president Harlan Barrows. In his address, he redefined geography as the study of human ecology. According to Barrows, geographic research in human ecology should abandon environmental determinism and focus on functional relationships between human activities and the natural environment (Barrows 1923). For him, this meant that geographers should focus their attention on problems, and functional relationships associated between human adjustments to the natural environment.

To accomplish this task, he divided geography into three sub-fields. First, he defined economic geography as the study of the direct consumption of natural resources, which alters the physical and cultural landscape. Second, he added political geography to describe the relationships among political attitudes, activities, institutions, and the natural environment. Third, he incorporated social geography to study the connections between societies and their natural environment.

Barrows's work has been interpreted as viewing the environment as a physical element rather than a spatial one (Zimmerer 1996). The process of turning Barrows's human ecology into the study of environmental hazards came into prominence with the work of his student, Gilbert F. White. Gilbert White integrated research on the physical elements of the environment with the human ecology that Barrows identified. The study of environmental hazards presented geographers with a way to research the relationship between economic damage, political interactivity, and social adjustment. This form of research led to the "self-conscious metamorphosis of Barrows's human ecology" into environmental hazards research (Zimmerer 1996: 166).

White studied under Harlan Barrows at the University of Chicago, the intellectual center of human ecology in American geography. White's research was the first definitive work on hazards integrating economic, political, and social areas that Barrows's work in human ecology had encouraged. White's work on the adjustment of human relationships to nature was influential in geography as well as in other research fields (O'Riordan 1986).

White's dissertation, the result of eight years of field observations, was completed in 1945 as *Human Adjustment to Floods: A geographical approach to the flood problem in the United States*. Through his research on relationships between human activity and nature, White developed a geographical methodology for studying environmental hazards, which advocated constructive legislative action by policy makers (White 1945).

The resulting analysis allowed White to interpret human relationships with the environment in part to follow Barrows' notion of examining what, when, and how rather than why people adjusted to an environmental event. Overall, hazard-appraisal and empirical data gathering on human adjustment not only established a reproducible research design for natural hazard analysis, but also a new direction in geographic research. The methodological framework created by White guided the study of environmental hazards, which later became the foundation for the hazard paradigm.

Hazards research aids policymaking decisions when using White's method of modeling how individuals and groups cope with the risk and uncertainty of environmental hazards (White 1973). Hazard geographers argued public policy planning efforts failed to properly plan for human adjustment to hazards because policy makers did not understand the hazard and the people they were planning for (White 1973, 1974). The work by White and his students, Ian Burton and Robert Kates, pursued public needs by informing policy makers on how to properly plan for human adjustments to hazards.

The Burton-Kates-White paradigm, as it is called (Watts 1983), guided geographers in their research methods, concepts, and hypotheses formation.

The Burton-Kates-White research paradigm incorporated five essential research concepts: (1) human occupancy estimation, (2) analysis of possible social adjustments, (3) examination of hazard perceptions, (4) examination of adjustment choices, and (5) estimation of public policy effects (Burton, Kates, and White 1993; White 1974). Through analysis of these concepts, five important hazard adjustment hypotheses have emerged to explain how hazards affect the human-environment relationship. The first argues that human occupancy in recurring hazardous areas exists because of superior economic opportunity, lack of satisfying alternatives, short-term planning, and high recovery against potential loss (White 1974). The second lists three types of response to natural hazards: folk/pre-industrial, modern technological/industrial and comprehensive/post industrial (White 1974). The third hypothesis is that hazard perception and estimation are determined by the magnitude and frequency of hazards, frequency of personal experience, income or attachment to location, and level of personal risk (White 1974). The fourth hypothesizes that the choices of adjustment are driven by hazard perception, personal choices, technology, economic efficiency, and social perceptions (White 1974). Finally, individual and group perceptions include anticipation of loss, power of government, and economic stability (White 1974).

Research methods used multiple hazard analysis, which tested hazard hypotheses during early hazard research and coincided with the Burton-Kates-White techniques of field observation and structured interviews. Field observations were designed to obtain detailed descriptions to examine the five essential research concepts. In addition, the basic interview identified individual and group perceptions, which aided in defining aspects of the hazard hypothesis. The observations and interviews used in hazard research developed into a system of decision analysis to identify risk and uncertainty for individuals and social groups. More importantly, these decisions aided the roles of local, national, and international government agencies in establishing public policy.

The information conveyed in hazard research was used to inform four policy foci: (1) disaster relief, (2) control of natural events, (3) comprehensive reduction of damage potential, and (4) combined multi-hazard management (Burton, Kates, and White 1993). These foci are part of a larger role for decision analysis used in public policies outlined in the Burton-Kates-White paradigm hazard research and analysis. The foci aid in policy decisions by first having policy makers to see hazards as a result of the interaction between human and physical systems, second using resources of a hazardous area for social benefits and third examining the circumstances of human adjustments and the adoption of alternative planning techniques (Burton, Kates, and White 1993).

The basic public policy concepts used planning adjustments for hazard-prone areas to provide relief and rehabilitation, to determine insurance coverage, to prevent loss, and to undertake land-use changes in light of hazardous events (Burton, Kates, and White 1993). The hazards paradigm used observation and interview techniques to allow geographers to determine human adjustments to guide hazard policies.

Hazard Paradigm Critiques

Beginning in the 1970's, critics of the dominant Burton-Kate-White hazard paradigm began to question its methods and direction. Geographers criticized the research design for its ecological conception of society and questioned its politicized view of hazard management (Zimmerer 1996). Critics further argued that the human ecology approach to hazard research was limited to analyzing adaptive strategies (how individuals think about environmental-related activities) and adaptive processes (how individual choices lead to patterns of environmental modification) (Zimmerer 1996). Porter (1978) argued that human ecology's objective in geography is holistic research conducted as a synthetic and directed analysis of populations, rather than the hazard paradigm's narrow adaptation research. Because hazard research is limited to adaptive strategies and processes, critics argued that it no longer fit into human ecology's ideas of progressive contextualization where research involves examining specific actions, tracing cause and effect, and remains committed to understanding a larger complex cause and effect in human-environment relationships (Vayda 1983). Critics began to see hazard research as being technocratic (Hewitt 1983), having a lack of solid theoretical ideas, (Watts 1983), and marginalizing poor societies (Wisner, Westgate, and O'Keefe 1976).

Hewitt's (1983) critique argued that technocratic ideas of calamity led geographers working in the hazard field to use their research and analysis to reflect governmental positions and private organization's requests. Moreover, because those requests were conducted under the guidelines and regulations of government and private organizations, the credibility of the evidence is only as good as its source (Emel and Peet 1989). This was considered a flaw in hazard research because government guidelines could distort the analysis based on self-interests. This union of science and bureaucracy to control policy was, argued by Hewitt, as hazard research being technocratic. Hewitt first argued that natural hazards are intractable problems for technocrats. Second, analyses by technocrats have subjective research objectives, which create misguided hazard research strategies. Third, because the technocratic strategy is inflexible, socio-cultural and geographical perspectives are lost. Finally, technocratic strategy is hierarchical where the most powerful states come first which depending on the level of power can distort the results and thus the effectiveness in hazard research goals (Hewitt 1983). In order to move away from the technocratic view, Hewitt suggests that hazard research take social organization into account, and encouraged analysis of ways that socio-political and economic aspects contribute to the social creation of disasters (Gares, Sherman, and Nordstom 1994; Hewitt 1983).

Watts (1983) argued that concepts and assumptions used in hazard research were limited to specific views of nature, society, and man. He further added that their assumptions of human-environment relationships lacked understanding of methods and theory. According to Watts, the theoretical link to hazards was in Marxist political and social theory. Watts argued that hazard research problems stem from human-environment relationships in two areas. First, the hazard paradigm analyzed people and nature as discrete entities, and second it contained neo-Darwinian characteristics of adaptation through particular biological features (Watts 1983). Accordingly, maladaptation is a human dysfunction that results from failures in hazard perceptions, knowledge, and decision-making (Emel and Peet 1989; Watts 1983). These maladaptations contributed to problems associated with a lack of political and social context in hazard research. Watts suggests that the Marx metaphor of labor and inter-subjectivity be used to fill political and social gaps in hazards research in human ecology (Watts 1983). The labor context relates to man's intentional modification of the environment is based on the knowledge of nature which is socially acquired, while the intersubjectivity relates to the social understanding of nature's subjects, which, according to Watts, is the relation between society and nature (Watts 1983). Watts' critique stimulated ecological questions within the hazards paradigm, which helped relate theoretical notions of socio-spatial context with a Marxist approach (Emel and Peet 1989).

Criticism of hazard research also identified problems of societal marginalization. The theory of marginalization, prevalent in urban/social geography, was used to view economic systems as the source of problems associated with people occupying hazardous areas. Critics argued that hazards research identifies hazards and their effects but failed to see patterns among the most affected populations. These areas are typically classified as overpopulated with minimal levels of resources and capital, which are not symptoms, but rather the effects of underdevelopment (Gares, Sherman, and Nordstom 1994). Marginalized populations caused environmental deterioration through (a) an increase of social, economic, and physical destruction, (b) continued suffering of the poorest, (c) constant disregard for relief assistance to the weakest, and (d) ineffectual social development programs (Emel and Peet 1989; Wisner, Westgate, and O'Keefe 1976). Geographers in the hazard field were criticized if they failed to emphasize historical and social problems in their research. This supposedly provided solutions involving large-scale socio-political change rather than implementation of small-scale adjustments (Gares, Sherman, and Nordstom 1994).

These criticisms led to the evolution of hazard research to address historical and social contexts of environmental risks (Zimmerer 1996). In addition, fueled by the argument that the early paradigm was too focused on physical events and not on social dysfunction and risk, hazard researchers had to understand the limitations of hazard research not only with their methodology but also with their capability to support and add to hazard knowledge (Gares, Sherman, and Nordstom 1994; Smith 2001).

Changes in Hazards Research

Critics of hazard research generated changes in the paradigm framework. While geographic research attempted to maintain its human ecological approach, other disciplines, such as psychology and sociology, were conducting research that emphasized behavioral aspects of the individual and community to improve hazard preparedness (Smith 2001). This dynamic division in hazard research caused geographers to reflect upon the research areas they were neglecting. They began including the concepts of environmental justice, risk, and vulnerability used by sociologists, and branched out from natural hazards to include technological, global, and other forms of hazards.

The study of technological hazards was in response to the increasing threat of toxic chemical exposure. For example, in the 1980's the threat of nuclear winter in the United States invigorated geographic research to investigate the potential for permanent environmental damage and irreconcilable social devastation (White 1988). Risk and vulnerability to nuclear exposure in the United States clarified spatial patterns in the social response to the threat of nuclear winter (Cutter, Holcomb, and Shatin 1986). Though the threat of nuclear conflict during the Cold War was the largest technological hazard, the majority of technological hazard geographers devoted more time examining patterns of toxic chemical exposure and contamination in populated areas.

The areas determined to be at risk for toxic releases were found to be influenced by urban and rural economics and transportation networks such as roads and railroads (Cutter and Ji 1997; Cutter and Solecki 1989; Hewitt 2000). Physical risk to technological hazard additionally determined social vulnerabilities. Investigations into social vulnerabilities focused attention on the social ramifications of technological hazards compared to earlier hazard research. Correlations between race and income and risk areas for toxic release were also found (Cutter, Scott, and Hill 2002; Cutter and Solecki 1989; Cutter and Tiefenbacher 1991).

These social effects were known as environmental justices, which helped explain how minority and low-income areas were purposely put at greater risk. The use of risk and vulnerability assessments in understanding the impacts of toxic release increased the use of decision-analysis in hazard research and showed how social risk can be amplified through communication during technological hazards (Pidgeon, Kasperson, and Slovic 2003).

Hazard research expanded to include global hazards. The use of large-scale globalization analysis encouraged the study of global hazards and disasters (Andrey and Hewitt 2000). These scale-dependent studies consisted of analyses of what hazards could cause large-scale disasters such as ozone depletion and global warming. Global-scale studies analyzed aspects of social risk and human vulnerability more holistically (Burton 1997). The analysis of how hazards affected social adjustment globally has encouraged political and economic reform in the reduction of hazards, especially technological hazards, which contribute to global warming, and ozone depletion (Turner et al. 1990).

The majority of early hazard analysis came in the form of conceptual models, such as Gilbert White's hazard adjustment and disaster planning agendas. The Burton-Kates-White method depicted hazard research goals on a very basic level. Much of the early modeling excluded the political, economic, and social issues that later critics would identify.

The use of conceptual models remains a part of the hazard paradigm analysis. Some models can be displayed geographically and incorporate ideas from older conceptual models and apply them to real world scenarios. Though not all conceptual models have a spatial component they remain a strong application in hazard research. Some examples of conceptual models are the hazards-of-place model, the pressure and release model, and access model.

The concept of hazardousness-of-place, originally developed by Ian Burton and Kenneth Hewitt, demonstrated that geography defined a population's risk to hazards (Hewitt and Burton 1971). Hazardousness-of-place examines components of social vulnerability by measuring the likelihood of a hazard event, risk mitigation, and location to hazards (Cutter 1996; Cutter, Mitchell, and Scott 1997). Then it identifies the importance of social experience, economic, and demographic characteristics in a community's response, recovery, and adaptation to hazards (Cutter 2003). It was not until Cutter (1996) that a conceptual model introduced hazardousness-of-place as a depiction of social vulnerability (Cutter 1996; Cutter, Boruff, and Shirley 2003; Cutter, Mitchell, and Scott 2000).

The pressure and release model (PAR) and access model explain social risk in terms of a specific hazard vulnerability (Wisner et al. 2004). The PAR model compared the processes of vulnerability (root causes, dynamic pressures, and unsafe conditions) to the characteristics and damages of a specific hazard and analyzed social reaction to specific hazard and disaster effects (Wisner et al. 2004). The access model expands on PAR by investigating "how vulnerability is initially generated by economic, social, and political process and what then happens as a disaster unfolds" (Wisner et al. 2004: 50).

Though models such as these can only attempt to capture real world attributes, they differed from earlier models by expanding the definition of vulnerability and risk. Models identifying vulnerability and risk also began to include physiological and sociological ideas, which examined behavioral aspects for analysis in recognizing potential solutions for disaster scenarios. One such example is the protective action decision model (PADM). This model uses decision theory and general systems theory to explore components of decisions and threats involved in mitigating a community's response (Lindell and Perry 1992, 2004; Tierney, Lindell, and Perry 2001).

Research Direction

The hazard paradigm concept, with its human ecological roots from Harlan Barrows, to technical assessment of vulnerability by Susan Cutter, continues to grow in geography. The earlier works by Gilbert White fueled geographic research in natural hazards and provided a basic framework for hazard research. Critical analyses from Kenneth Hewitt and Michael Watts identified crucial gaps in the field. Those gaps have been filled with research beyond natural hazards, including technological and willful hazards. The methods used to analyze hazard research now include advanced modeling and technological applications such as GIS. The hazards paradigm in geography today continues to utilize Harlan Barrows's human ecology tradition to analyze human-environment relationships.

The current trend of geographic research analyzes vulnerability and risk using geographic information technology. The trend is partly credited to the Robert T. Stafford Disaster Relief and Emergency Assistance Act, which recognized the need to conduct vulnerability studies to improve the distribution of aid. Today, the use of GIS and other geographic information technology is standard in relaying vulnerability information to government officials and the public (Tobin and Montz 2004). Geographic information technology has allowed hazard researchers not only to display the elements of the hazard cycle but to more accurately calculate and assess patterns of vulnerability (Tierney, Lindell, and Perry 2001; Tobin and Montz 2004)

As the use of geographic technology increased, problems with using, obtaining, presenting, and maintaining spatial data soon began to arise (Bankoff, Frerks, and Hilhorst 2004; Carrara et al. 2000; Cutter 2003; Goodchild 2003; Longley et al. 2005; Perotto-Baldiviezo, Thurow, and Smith 2004). Nevertheless, the potential value of geographic information technologies, such as GIS, is critical to aid in fast, effective problem solving. Uses of geographic information technology include: (1) studying GIS in emergency management, (2) examining GIS as a tool to understand disaster-related phenomena, (3) using GIS to test disaster-related survey results, (4) using GIS to better understand the social aspects of disasters, and (5) improving vulnerability analysis (Dash 2002). As research continues to develop in these areas, advances in data creation and manipulation will permit modeling of the spatial-temporal distribution of physical impact and human reaction to hazards with an emphasis on creating more realistic models that fuse impact, response, and perception (Alexander 2000).

As research using geographic information technology progresses, conceptual models will be replaced with more realistic models of the spatial-temporal distribution of physical impact and social vulnerability (Alexander 2000). For example, geographic information technology in hazard research has led to advanced flow models for recording landslides (Carrara et al. 2000), real time volcanic mapping (Honda and Nagai 2002), and urban flooding (Zerger and Wealands 2004). The use of geographic information technology has also led to web-based GIS and use of remote sensing in analyzing mitigation, response, preparation, and recovery during a hazard event (Chen et al. 2003; Kerle and Oppenheimer 2002; Robson 2003; Vassilopoulou et al. 2002; Zerger and Smith 2003).

The development of models for analyzing hazards and social vulnerability has not been an easy task as the concept of vulnerability is very complex. Cutter (2001) argued that vulnerability is not uniform in terms of the spatial distribution of susceptibility and impact on a society. This is important because if a population's vulnerability varies spatially neither will a population's capacity to recover. Furthermore, information is required to actually measure a population's vulnerability, some of which has never been collected (Cutter 2001). This study will continue to address the challenge of using geographic information technology in hazard research by adding the knowledge of social vulnerability models.

CHAPTER III

METHODOLOGY: SOCIAL VULNERABILITY MODELING

Geographic information technology is a vital tool for measuring hazard vulnerability. It analyzes hazard information spatially, emphasizing place and the populations involved. This study uses geographic information technology, particularly GIS, to test if using census blocks (CBLK) rather than census block groups (CBG) provides a more exact measurement of social vulnerability. This is done by first testing if a countywide SVI is more exact if using CBLK rather than CBG, second if a municipal wide SVI is more exact if using CBLK, and lastly if using CBLK with a potential hazard shows a population's social vulnerability better than CBG.

To test these hypotheses this study uses a series of procedures. The first calculates and maps social vulnerability for a county using CBG. The second recalculates and maps social vulnerability for the county using CBLK. The third procedure calculates and maps social vulnerability for those CBG and CBLK that lie within or intercept the city limits. Lastly, to take the results of the third procedures to examine if CBLK more exact measurement of social vulnerability can be applied to a local hazard, in this case a train derailment.

Study Site

The social vulnerability analysis is undertaken for Brazos County, Texas (Figure 2). Brazos County is located 225 kilometers miles north of the Gulf of Mexico in Central Texas between the Brazos and Navasota Rivers. The county's vegetation is Post Oak

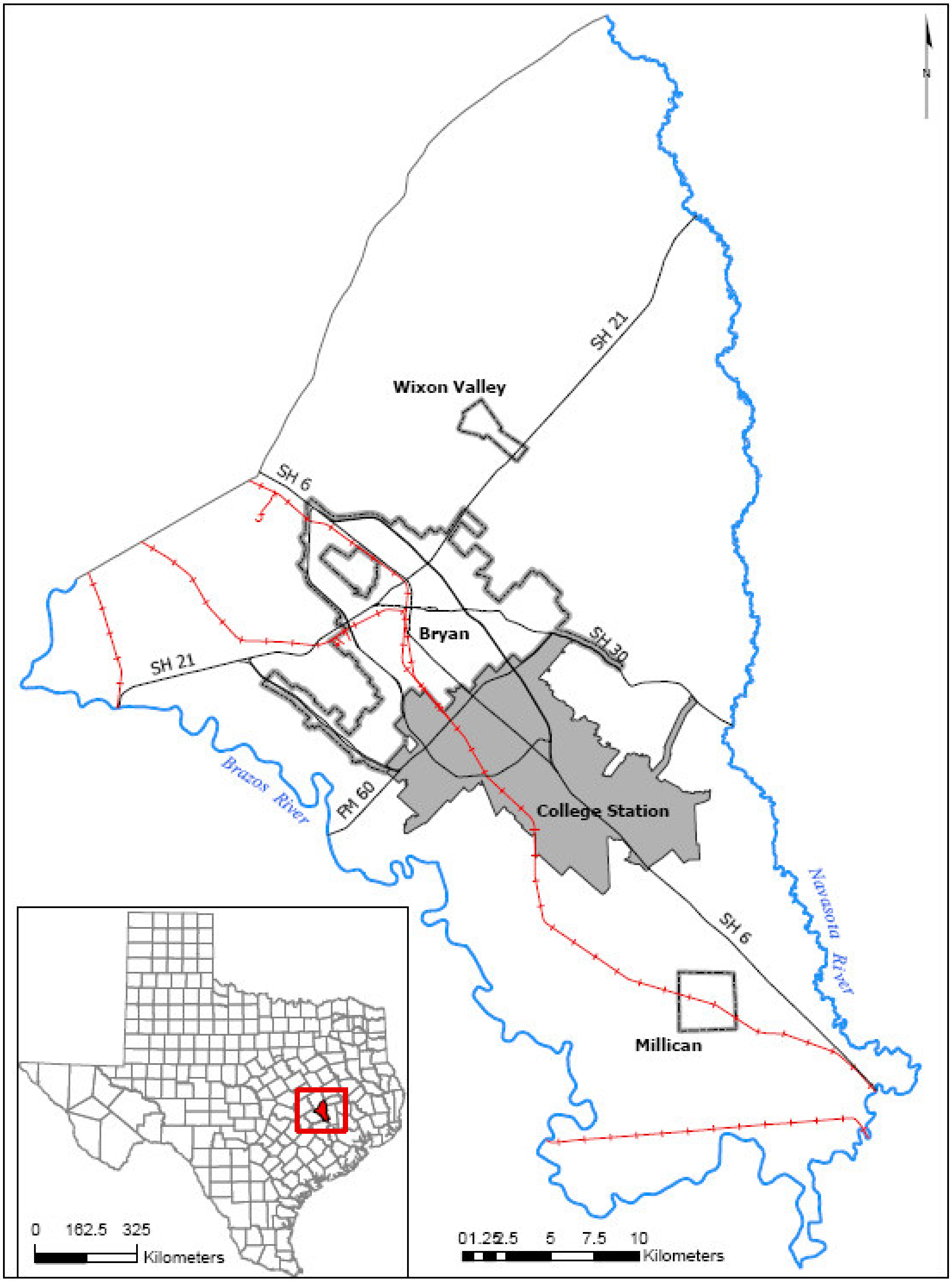

Figure 2. Study site of Brazos County, Texas

Savanna with rich bottom and sandy clay soils. The county has an area of 1,530 square kilometers, including 13 square kilometers of water. The elevation ranges from 61 to 122 meters above sea level. In 2000, Brazos County had a population of 152,415 spread throughout the county and its incorporated cities. The two largest cities are Bryan (pop. 65,660) and College Station (pop. 67,890) and contain the majority of the county's population. The rest of the Brazos County population spreads throughout the county in smaller incorporated municipalities including Wixon Valley (pop. 235), Millican (pop. 108), and Wellborn (pop. 100).

The municipal study site is the city of College Station. College Station covers an estimated 106 square kilometers with a population of 67,890. The growing population in College Station is due mainly to Texas A&M University. Texas A&M University is a home for many students and is surrounded by student-oriented housing. The university has created a diverse and international population in a pocket of the city, which may affect the city's vulnerability calculations and resulting maps.

Choosing Brazos County as the study site is reasonable because it is a destination site for Gulf Coast hurricane evacuees. A social vulnerably assessment for the county could help Brazos County and its local municipalities to determine the locations for displaced persons without increasing their own social vulnerability. The reason for choosing College Station was chosen as the study municipality because it is the largest municipality in the county and because this study is a cooperative project with College Station. The College Station Emergency Management Department lacks the time and personnel to measure and map social vulnerability. This study relies on GIS resources and cooperation from College Station's Department of Planning and Development Services, Department of Water/Waste Water, Department of Public Works and the Office of Technology Information Systems.

Method for Calculating Vulnerability

In 1997, the Hazard Research lab of the University of South Carolina's Geography Department published a document detailing the use of geographic information technology for performing vulnerability assessments. The assessment method was based on Federal Emergency Management Agency (FEMA) standards for countywide hazard identification. It incorporated CBG demographic information to calculate social vulnerability. This document by Cutter, Mitchell, and Scott (1997) advised that countywide hazard assessment should combine information concerning physiographic characteristics relevant to hazards and social demographics to identify the most vulnerable places within a county. The most significant part of the Cutter, Mitchell, and Scott (1997) study was the use of geographic information technology to conduct the social vulnerability assessment. In hazard analysis, geographic information technology had been limited to physical assessments such as mapping landslides and volcanic activity while social assessments were conducted through interviews and displayed in figurative and conceptual models. The Cutter, Mitchell, and Scott (1997) method developed a spatial component to social vulnerability studies and integrated geographic information technology into hazard research for more social analysis.

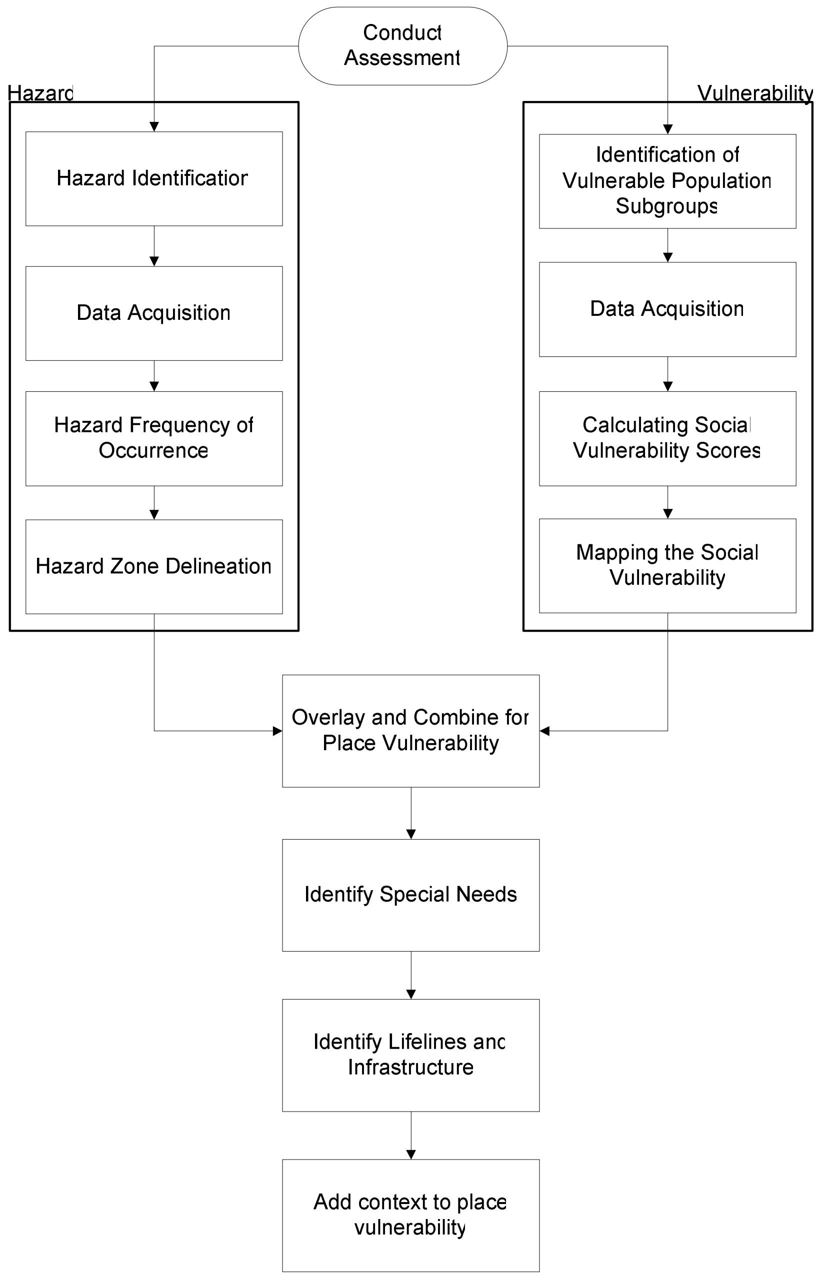

Figure 3. Vulnerability Assessment Procedure. (Modified from Cutter, Mitchell, and Scott 1997)

The Cutter, Mitchell, and Scott (1997) hazard assessment method (Figure 3) has three main components: (1) hazard occurrence, (2) social vulnerability, and (3) overall place vulnerability. In the first component, hazard occurrence measures the biophysical vulnerability, which refers to physical exposure to and proximity of hazardous conditions such as magnitude, duration, frequency, and impact from environmental hazards (Hill and Cutter 2001). The first component measures biophysical vulnerably in three steps. The first step identifies hazard potential by determining the range of local hazards that could occur within area. This requires historical research to identify recent and past hazards. The second step, acquisition of data, relates hazard information to a specific spatial location. The third step calculates the estimated hazard frequency within the area by computing the recurrence interval. These three steps create a composite hazard zone map, which presents a numerical score based on the hazard frequency. The composite map takes overlapping hazard zones and combines them so that areas that have multiple hazards will have a higher rate of occurrence.

The second component in the Cutter, Mitchell, and Scott (1997) method calculates social vulnerability. This second component is a companion to the first. Instead of analyzing the physical characteristics of vulnerability, it analyzes the characteristics of social groups that make a population vulnerable to hazards. The social group variables used in county analysis consisted of total population, number of non-whites, number of females, number of people less than 18 years of age, number of people over 65 years of age, number of housing units, and median housing value. Total population identifies the total number of people in each areal unit and can be used to calculate population density. Number of non-whites identifies a segment of the population that is more likely to need emergency resources. Furthermore, non-whites are more likely situated near potential dangerous industrial centers and transportation networks making them more vulnerable to the effects of accidents that occur there (Cutter, Mitchell, and Scott 1997; Lindell and Perry 2004). Besides race, age and gender can also affect a population's vulnerability. Females may be more vulnerable because they have limited adjustments in an emergency (Cutter, Boruff, and Shirley 2003; Cutter, Mitchell, and Scott 1997). Females are particularly vulnerable to technological hazards, which can cause adverse health problems potentially destroying their ability to have children (Cutter, Boruff, and Shirley 2003). Populations under 18 and over 65 years of age have limited mobility to evacuate a hazardous area and can slow down recovery after a disaster because they require much more attention. (Cutter, Mitchell, and Scott 1997). Knowing the number of housing units aids in indicating where the greatest number of people reside. The median housing value is one way to determine the economic status of individuals and their ability to recover after a hazard. Lower the housing value typically means lower economic status, and thus a lower ability to recover.

Social vulnerability is determined by calculating the percentage of every variable for each CBG. The percentages are normalized to determine every variable's Social Vulnerability Indicator (SV) for each CBG. The SVs for each CBG are combined to create the Social Vulnerability Index (SVI). The first calculation in the process finds the percentage of each variable. This calculation used for CBG, excluding median housing value, is expressed as:

$$\left[X = \frac{a}{b}\right]$$

where *a* represents the value of the variable for the CBG and *b* represents the total value of that variable for the entire county. For example, from a county of 93 CBG, one CBG has a female population of 1,435 (*a*) and the entire county has 75,432 females (*b*) then the percentage (*X*) of females in that particular CBG would be 0.019. The next step is to calculate the SV, which is expressed as:

$$\mathrm{SV} = \frac{X}{X_{\max}}$$

where X represents a CBGs individual variable's percentage divided by X_{max}, the greatest percentage for any the CBG in the county. This normalizes the percentage to yield an indicator score between 0 and 1. Continuing with the pervious example, 0.019 would represent X. If the greatest value or X_{max} for the Female variable is 0.059, the SV for this particular CBG would be 0.32.

The only variable that does not use this formula is median housing value. Through analyzing the median housing value it can be assumed, according to Cutter, Mitchell, and Scott (1997:16), that "lower house values may indicate a more vulnerable population due to lack of resources for mitigation and recovery or housing that is of a lower structural quality." In calculating the SV for the median housing values, the first step in determining the difference between the county average median housing value (*c*) and the CBG median housing value (*d*), which is computed as:

$$A = c\text{-}d$$

This value is then scaled to remove negative values as follows:

$$B = A + |A_{\max}|$$

where A_{max} is the greatest value for any CBG. The final step is to calculate the SV, expressed as:

$$\mathrm{SV} = \frac{B}{B_{\max}}$$

where B_{max} is the greatest value of *B* for any CBG. For example, out of 93 CBG one the CBG of interest has a median housing value of $140,400 (*d*) and the average median housing value for the county is $77,626 (*c*) making (*A*) -$62,774. To compute *B*, add -$62,774 (*A*) to the maximum absolute value $141,974 ($A_{max}$) yielding $79,200. Finally, to calculate for SV, divide $79,200 (B) by $219,600 ($B_{max}$) resulting in an SV of 0.36.

After calculating the social vulnerability scores for each CBG, the scores are summed to form a final Social Vulnerability Index (SVI):

$$\mathrm{SVI} = \mathrm{SV}_1 + \mathrm{SV}_2 + \mathrm{SV}_3 + \ldots.\ \mathrm{SV}_n$$

Mapping these index scores illustrates social vulnerability across the county, highlighting the location of high and low score areas, where social groups are most and least vulnerable to any hazard, respectively.

After the completion of steps one and two, the third component of the Cutter, Mitchell and Scott (1997) method is to intersect the results of hazard occurrence and social vulnerability to create a composite map of overall hazard vulnerability. This information is then mapped for the entire county by multiplying the scores from the hazard occurrence zone and social vulnerable layers.

Social Vulnerability Research Method

The Cutter, Mitchell, and Scott (1997) method used three components, hazard occurrence, social vulnerability and overall hazardousness of a place, to analyze vulnerability. This study only considers social vulnerability. The first procedure calculates and maps social vulnerability at a county level using the original Cutter, Mitchell, and Scott (1997) method with CBG. This includes using similar variables – age groups over 65 and under 17, non-white, females, number of housing units, median housing value, and total population and number of households. Number of households takes into account the number units that are identified as an occupied household, either owner occupied or renter occupied. The reason is that houses that are owner occupied housing, depending on the hazard event may have difficulty recovering due to problems with owner who abandon or sell their house. Also, owners' ability to leave an area is more difficult. Homeowners usually have higher incomes and better access to credit than do renters, both of which are important during disaster recovery (Peacock 2003; Wisner et al. 2004). In addition, much of the assistance available to individuals is targeted to homeowners rather than renters, who frequently lose all their belongings, receive little compensation, and must seek housing in a tighter rental market (Lindell and Perry 1992, 2004; Tobin and Montz 2004; Wisner et al. 2004).

The second procedure recalculates and maps social vulnerability at a county level using CBLK. The same variables are used. The difference is the spatial scale of the CBLK. In the 2000 Census, the United States Census Bureau reported three types of aggregated data, tracts, block groups, and blocks to show geographic distribution of the population's characteristics in some detail. The census tract contains between 3,000 and 8,000 residents for each tract. CBG contains between 600 and 2,500 residents and is the most widely used form of aggregated data in hazard assessments (Cutter, Mitchell, and Scott 2000). CBLK are aggregated at the smallest geographic scale and are based on individual city blocks usually bound by city streets.

Third, this study calculates and maps social vulnerability based on only those CBG and CBLK that fall within or intercept the College Station city limit. One of arguments raised in this study is that social vulnerability assessment using CBG is not suitable for municipalities. In the case of College Station, limiting social vulnerability calculations to the city limits eliminates the unincorporated areas that could possibly change the SVI. Again, each of the demographic variables will have the SVI calculated and mapped to show social vulnerability for CBG and CBLK.

The last procedure uses the results from the municipal CBG and CBLK to determine how social vulnerability assessment will differ for a local hazard threat. The hazard that will be examined is a train derailment within the city limits of College Station. A train derailment is a significant local hazard because College Station contains a stretch of Union Pacific Railroad, which has caused concerns because of the potential hazards. In addition, a train derailment has the potential for causing a greater amount of damage to the city and its residents compared to other hazards in the area. The rail line runs through the Texas A&M Campus, College Station's highest concentration of people and its economic livelihood.

Brazos County and College Station emergency managers designated a standard one-half mile evacuation limit. The areas most at risk from a train derailment will be overlaid on the social vulnerability maps constructed from each of the data sets to determine if CBLK provides a more exact measurement and mapping of socially vulnerable persons within the evacuation limit.

Through mapping social vulnerability, this study seeks to determine if CBLK yields a more precise measurement of SVI than CBG. This study is an attempt to show that CBLK data is superior to CBG because it provides a more exact measurement or vulnerability. This is important because the maps that emergency officials rely on to determine strategies in emergency management result from this analysis.

CHAPTER IV

RESULTS OF SOCIAL VULNERABILITY ANALYSIS

The results of the social vulnerability analysis demonstrate, in the following three sections, that census block (CBLK) data are superior to census block group (CBG) data for analyzing social vulnerability. The first section shows the overall Social Vulnerability Index (SVI) computations for CBG and CBLK. This section tests whether using CBLK is more accurate than CBG for conducting a social vulnerability analysis at a countywide scale. The second section shows the overall SVI computations focusing on the city of College Station. These results test whether, in a municipal-wide social vulnerability analysis, the SVI computations using CBLK are more exact than CBG. The last section examines the potential for a train derailment hazard overlaid with the overall CBLK and CBG social vulnerability. These results will help test if using CBLK overall social vulnerability for a potential hazard can better identify the at-risk population's variability than CBG.

All results were visually analyzed by their overall SVI level of vulnerability. All SVIs were mapped on a continuous scale using natural breaks. Cutter, Mitchell, and Scott (1997), suggested this scale and categorical grouping when mapping social vulnerability. Their maps, like those presented here, use lighter colors to indicate low concentrations of social vulnerability and darker colors to show high concentrations of social vulnerability.

CBG and CBLK spatial aggregations are different, creating the potential for important spatial differences to exist between them and be affected by the Modifiable Areal Unit Problem (MAUP). This means relationships between variables can change with differences in the level of aggregation (Openshaw 1984; Openshaw and Taylor 1982). Specificly, the zoneation effect is the deviation in numerical results arising from the grouping of small areas into larger units (Openshaw and Taylor 1979). From the MAUP, we can infer that, because CBLKs are smaller, they are less likely to mask meaningful geographic variations than the large CBGs. On the other hand, the zoneation effect states that when using a smaller spatial aggregation like CBLKs, the analysis may tend to provide unreliable results because the sample size of the units is smaller (Goodchild 2003).

Related to the MAUP is the concept of ecological fallacy which describes an interpretation of results as having false relationships between levels of spatial aggregation (Barber 1988; Bednarz and Tenfjord 1997; Tenfjord 1998). The most serious ecological fallacy is interpreting areal units as having homogenous relationships when in fact they do not (Barber 1988; Bednarz and Tenfjord 1997; Goodchild 2003). Larger areal units such as CBG can mask internal population variation, which could cause a misinterpretation of an area's population in a particular SVI. This can affect emergency planning and cause confusion during a hazard event by having first responders mistakenly evacuate groups who do not need help, and, conversely, overlook those who do. This is a problem with geographic data that cannot be corrected even in a situation where there is an optimal level of aggregation (Goodchild 2003; Openshaw and

Taylor 1982). Though problems in data aggregation can cause errors in data analysis, the geographically smaller CBLKs should provide a more accurate analysis of social vulnerability than CBGs.

Countywide Social Vulnerability Results

Brazos County has 93 CBGs and 2,888 CBLKs. The breakdown of the total, minimum, maximum and mean of important demographic variables is listed in Tables 1 and 2, which begin to show some of the differences in aggregation. CBG have larger mean, minimum and maximum ranges than CBLKs. The larger ranges and means compared to the smaller ranges in CBLKs show the potential for CBGs to mask meaningful geographic variations in the social vulnerability analysis.

Table 1. Brazos County Census Block Groups Demographics

Demographics	Total	Mean	Min	Max
Total Population	152,415	1,638.87	502	9,742
Non-White	38,936	418.67	47	1,360
Female	75,432	811.10	244	4,471
Age Under 18	32,735	351.99	29	1,131
Age Over 65	10,223	109.92	1	513
Households	55,202	593.57	8	2,076
Housing Units	59,023	634.66	8	2,338
Median Housing Value		$77,984	$11,100	$219,600

Table 2. Brazos County Census Block Demographics

Demographics	Total	Mean	Min	Max
Total Population	152,415	52.78	0	4,448
Non-White	38,936	13.48	0	610
Female	75,432	26.12	0	1,609
Age Under 18	32,735	11.33	0	415
Age Over 65	10,223	3.54	0	273
Households	55,202	19.11	0	678
Housing Units	59,023	20.44	0	818
Median Housing Value		$76,299	$11,100	$219,600

The CBG map (Figure 4) shows the continuous scale of social vulnerability for the 93 census block groups in Brazos County. Numerically, the social vulnerability values range from 1.02 to 4.39. Low and high values were chosen based on their location within the social vulnerability range. The low social vulnerability group, ranging from SVI values of 1.02 to 1.58 contains those CBGs in the lowest of the five natural breaks. High values of social vulnerability ranged from 3.37 to 4.39, the highest break. Using the two extremes of high and low helps with the comparison between CBGs and CBLK because they have different numerical values of vulnerability. By using the two categories we make our SVI comparisons based on those lowest and highest values without subjecting it to a more complex ranking schemes which might not help when comparing these two groups.

Out of the 93 CBGs, 12 have low concentrations of social vulnerability and 9 CBGs have high concentrations. Tables 3 and 4, list the low social vulnerability CBGs have smaller totals, means, minimums, and maximum values than the high CBG areas.

Table 3. CBG Values of Low Social Vulnerability between 1.02 to 1.58

Demographics	Total	Mean	Min	Max
Social Vulnerability		1.36	1.02	1.58
Total Population	9,262	772	502	1,037
Non-White	1,731	144	60	308
Female	4,396	366	244	530
Age Under 18	1,919	160	34	359
Age Over 65	513	43	7	103
Households	3,514	293	131	479
Housing Units	3,692	308	145	504
Median Housing Value		$94,867	$48,300	$139,100

Table 4. CBG Values of High Social Vulnerability between 3.37 to 4.39

Demographics	Total	Mean	Min	Max
Social Vulnerability		4.03	3.63	4.39
Total Population	36,942	4,105	2,349	9,742
Non-White	7,865	874	279	1,360
Female	18,472	2,052	1,168	4,471
Age Under 18	5,151	572	29	1,131
Age Over 65	893	99	1	196
Households	10,841	1,205	8	2,076
Housing Units	11,622	1,291	8	2,338
Median Housing Value		$78,333	$11,000	$165,900

Median housing values show that the average housing value is much higher, and its lowest value is almost quadruple that of the minimum value in the highest social vulnerability area. This is because having a low median housing value SVI means the housing value is high, showing greater ability to recover after a disaster, while a high SVI means the housing value is low with correspondingly lower ability to recover. The largest concentrations of vulnerability appear to contain high concentrations of the total population, females, households, and housing units, in contrast to areas of low vulnerability.

In Figure 4, both high and low vulnerability concentrations either intersect or are within the Bryan and College Station city limits. However, because of the large aggregation of CBGs, it is difficult to determine if rural and urban areas affect social vulnerability. By using CBLKs, it is expected that the smaller aggregation size will help to distinguish how each of the indicators influences overall social vulnerability and determine whether there are any differences caused by rural and urban areas.

The CBLK map (Figure 4) shows the social vulnerability values for the 2,888 CBLK in Brazos County. These social vulnerability values range from 0.01, the lowest, to 4.82, the highest.; 349 of the 2,888 CBLKs have low concentrations of social vulnerability (0.01 to 0.54) and 32 have high concentrations (between 2.28 to 4.82). The larger CBLK range gives a measurement output with a higher sensitivity to social vulnerability than CBGs.

Tables 5 and 6, like the CBG Tables, list the low social vulnerability CBLKs having smaller totals, means, minimums, and maximum values than the high CBLK areas. The small size of CBLKs show smaller population concentrations than the CBG ranges, thus CBLKs capture those areas with very high median housing values (low vulnerability).

The tables and maps show that CBLKs with high social vulnerability values are located within CBGs with high social vulnerability values. However, the difference between CBG/CBLK means, minimums, and maximums values again shows how the CBLKs allow a more sensitive and geographically exact measurement of social vulnerability, thus CBLK maps display more heterogeneity among individuals and groups in high and low social vulnerability areas. This is exemplified in Figure 4.

Table 5. CBLK Values of Low Social Vulnerability between 0.01 to 0.54

Demographics	Total	Mean	Min	Max
Social Vulnerability		0.38	0.01	0.53
Total Population	4,522	13	0	171
Non-White	2,089	6	0	151
Female	2,295	7	0	86
Age Under 18	1,208	3	0	53
Age Over 65	441	1	0	22
Households	1,665	5	0	70
Housing Units	1,754	5	0	71
Median Housing Value		$146,968	$109,850	$219,600

Table 6. CBLK Values of High Social Vulnerability between 2.28 to 4.82

Demographics	Total	Mean	Min	Max
Social Vulnerability		3.01	2.35	4.82
Total Population	30,567	955	395	4,448
Non-White	388	12	0	98
Female	15,273	477	11	1,609
Age Under 18	4,279	134	4	415
Age Over 65	1,151	36	0	273
Households	9,815	307	0	678
Housing Units	10,643	333	0	818
Median Housing Value		$64,961	$11,100	$165,900

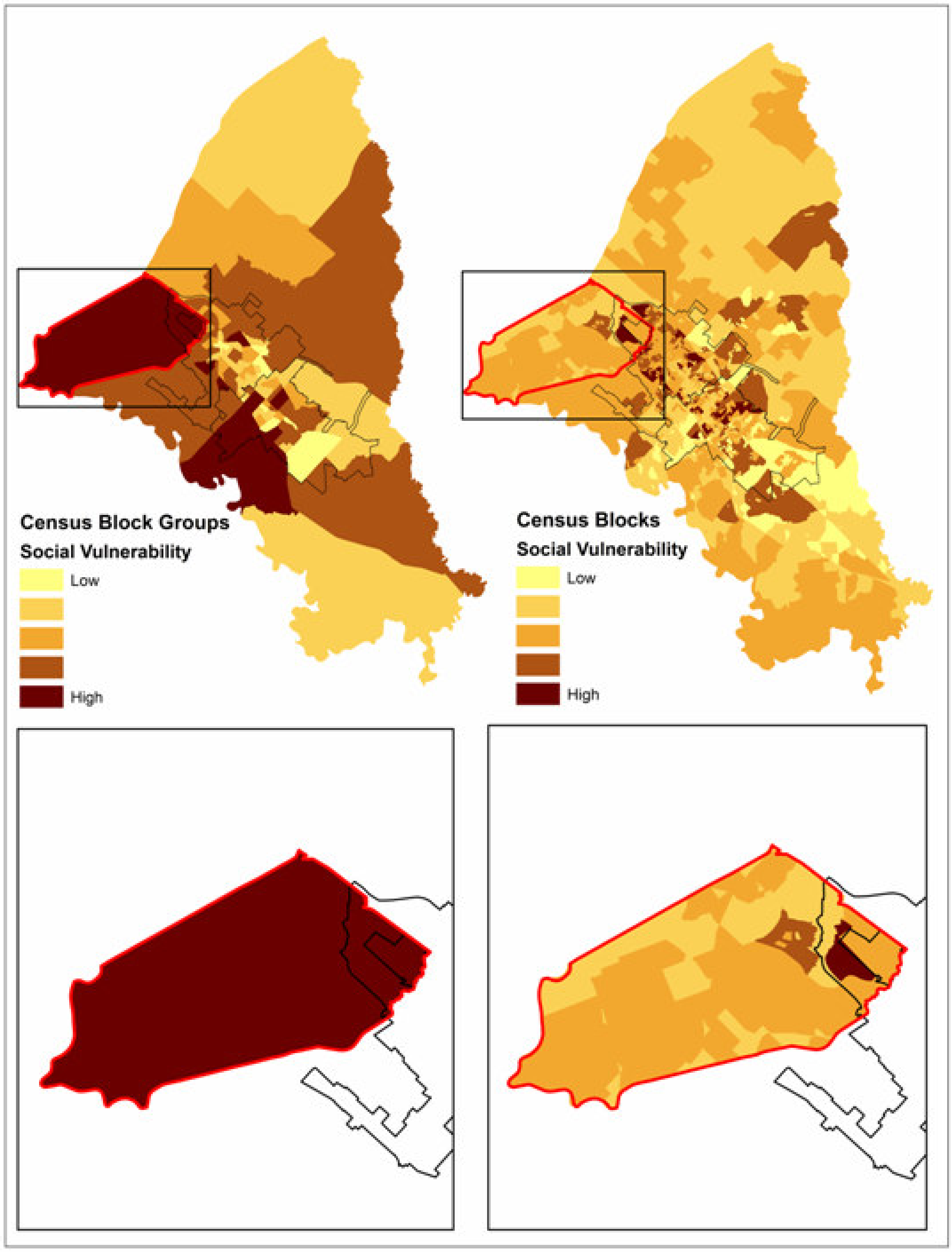

Figure 4. Brazos County CBG and CBLK Results

Like CBG results, the CBLK data have their highest and lowest concentration of social vulnerability either intersecting or within the Bryan/College Station city limits. However, in CBLK results, only the highest vulnerability concentrations are within the city limits while the lowest are spread around the southern parts of College Station and Brazos County. This means that spatial variations of urban social vulnerability, as mapped by CBLKs, are much higher than those of rural areas, as can be seen in the western “panhandle” region of Brazos County (see Figure 4).

According to the CBG map, this entire area is one CBG which has the highest concentration of social vulnerability due to high non-white and low median housing values. However, in the CBLK map of the 150 blocks that made up that one CBG, the highest concentration of social vulnerably is found within Bryan city limits. This high concentration is due to a large number of non-whites and low median housing values. Areas outside the city limits do not have high concentrations, due to lower total population with very small pockets of non-whites as well as other indicators. This is because the land around the Brazos panhandle is predominantly rural and agricultural. The sensitivity and more geographically precise results of CBLK capture the variability in the metropolitan areas with a denser population and diverse social groups where CBGs cannot. The lower concentrations of SVI outside the city limits show the rural areas as having less population density and thus less variability within those CBLKs.

The reason for this sensitivity is, again, the level of aggregation where CBGs have a much larger aggregated area than CBLKs. The largest CBG covers 239.86 sq km (59,271 acres), while the largest CBLK covers only 35.19 sq km (8,696 acres). The

CBG, because of its larger spatial aggregation, has less ability to capture variations in an area's demographics. This means that, unlike CBLKs, CBGs are unable to distinguish variability and therefore indicate an unrealistic level of homogeneous demographic qualities in the area. This bolsters the argument that that the smaller aggregation of CBLKs is a more accurate depiction of social vulnerability because they do not mask meaningful geographic variations. In addition, as illustrated in Figure 4, CBLKs have the ability to distinguish between rural and urban social vulnerabilities.

The evidence presented in this section is based on visual evidence of each SVI and of overall social vulnerability. The maps have shown that there is much more mapped spatial variability when using CBLKs than when using CBGs. This greater spatial variability shown in the CBLK data correctly identified Bryan and College Station as having higher concentrations of vulnerability than rural Brazos County. Furthermore, using a larger population in a larger geographical area such as in a CBG creates more error perhaps resulting in an ecological fallacy. The larger geographic area may increase the possibility of mistakenly inferring a population's homogeneity.

Municipal-Wide Social Vulnerability Results

Countywide social vulnerability results show major SVI variability in the urban areas of the county. This section focuses on a particular urban area, the city of College Station. Using the SVI computations, this section demonstrates that, in a municipal-wide social vulnerability analysis, the use of CBLKs results in a more exact SVI computation. Because this section focuses only on College Station, the SVIs are based on only those CBGs and CBLKs that are within or intersect the city limit. This eliminates those Brazos

County CBGs and CBLKS that are not related to those CBGs and CBLKs within College Station.

College Station contains 47 CBGs and 774 CBLKs. The breakdown of the total, minimum, maximum and mean of the demographic variables is listed in Tables 7 and 8. As in the county results, the CBLK ranges show a more sensitive account of social vulnerably measurement and therefore will provide more geographically exact locations of those areas in the city where social vulnerability is the highest and lowest. Based on the values for high and low concentrations of vulnerability for the county, this study assumes that the same results will occur when using just those CBGs and CBLKs that are within or intersect College Station. This then means that instead of using Brazos County (countywide) analysis this section will use the data for College Station to conduct a municipal-wide analysis of social vulnerability.

Table 7. College Station CBG Demographics

Demographics	Total	Mean	Min	Max
Total Population	90,546	1,926.51	567	9,742
Non-White	17,200	365.96	47	1,360
Female	44,240	941.28	246	4,471
Age Under 18	15,055	320.32	29	839
Age Over 65	4,063	86.45	1	243
Households	33,872	720.68	8	2,076
Housing Units	35,847	762.70	8	2,338
Median Housing Value		$92,960	$11,100	$219,600

Table 8. CBLK Demographics for College Station

Demographics	Total	Mean	Min	Max
Total Population	73,709	95.35	0	4,448
Non-White	13,420	17.36	0	610
Female	35,928	46.48	0	1,609
Age Under 18	11,061	14.31	0	379
Age Over 65	2,854	3.69	0	128
Households	27,152	35.13	0	678
Housing Units	28,610	37.01	0	818
Median Housing Value		$103,879	$11,100	$219,600

In Chapter I, there was a discussion of the importance of municipal-wide social vulnerability analysis. Tables 9 and 10 show how aggregation in CBLKs provides a more accurate depiction of the populations' demographics than CBGs. Using the 2000 Census demographics, we can examine how the overall College Station social vulnerability results, computed in CBGs and CBLKs, match the overall city demographics. Figure 5 illustrates that CBLKs are a better match with the city demographic data than CBGs. The difference between the College Station population figures and the computed CBG city population results is 22,656 (Table 9), which represents the number of additional people in its social vulnerability analysis. On the other hand, the CBLK computed data for College Station differ from the actual population by 5,819 persons (Table 10). Therefore, the CBLK aggregation is more representative of College Station demographics than CBG aggregation.

As the CBLK results aggregated population is closer to the actual city population, errors caused by including rural populations (non-College Station residents) are maximized in the social vulnerability analysis. The CBG obviously included more rural populations because of the greater level of spatial aggregation. Based on the city of College Station's population, by using CBLKs the municipal-wide social vulnerability assessment should provide a more sensitive and geographically exact computation figure than CBGs.

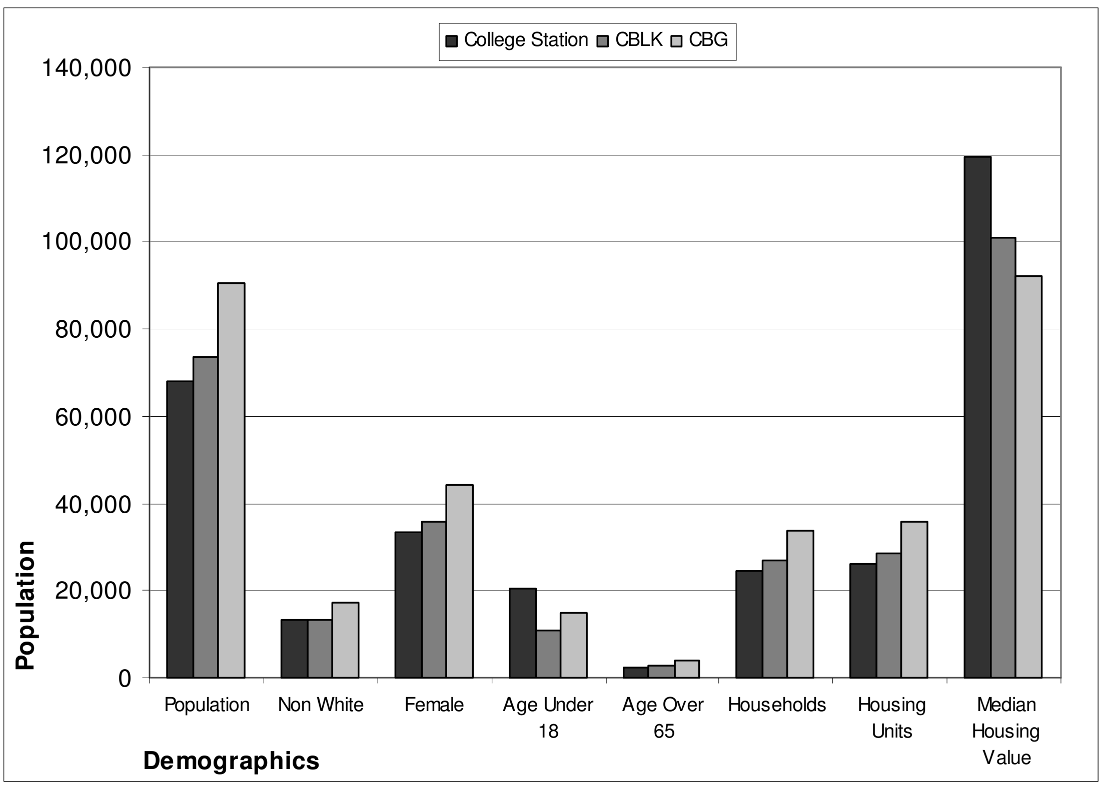

Figure 5. Demographic Difference Between College Station, CBLK, and CBG

Table 9. College Station CBG Differences in 2000 Census Demographics

Demographics	College Station	CBG	Difference
Total Population	67,890	90,546	-22,656
Non-White	13217	17,200	-3,983
Female	33,223	44,240	-11,017
Age Under 18	20378	15,055	5,323
Age Over 65	2,461	4,063	-1,602
Households	24,691	33,872	-9,181
Housing Units	26,054	35,847	-9,793
Median Housing Value	$119,500	$92,200	$27,300

Table 10. College Station CBLK Differences in 2000 Census Demographics

Demographics	College Station	CBLK	Difference
Total Population	67,890	73,709	-5,819
Non-White	13217	13,420	-203
Female	33,223	35,928	-2,705
Age Under 18	20378	11,061	9,317
Age Over 65	2,461	2,854	-393
Households	24,691	27,152	-2,461
Housing Units	26,054	28,610	-2,556
Median Housing Value	$119,500	$101,100	$18,400

This again can be illustrated by selecting key CBGs and those CBLKs within in them. Figure 6 shows the two CBGs intersecting the College Station city limits used in the SVI calculations. It also shows the 79 CBLKs that intersect College Station's city limits and make up the two CBGs.

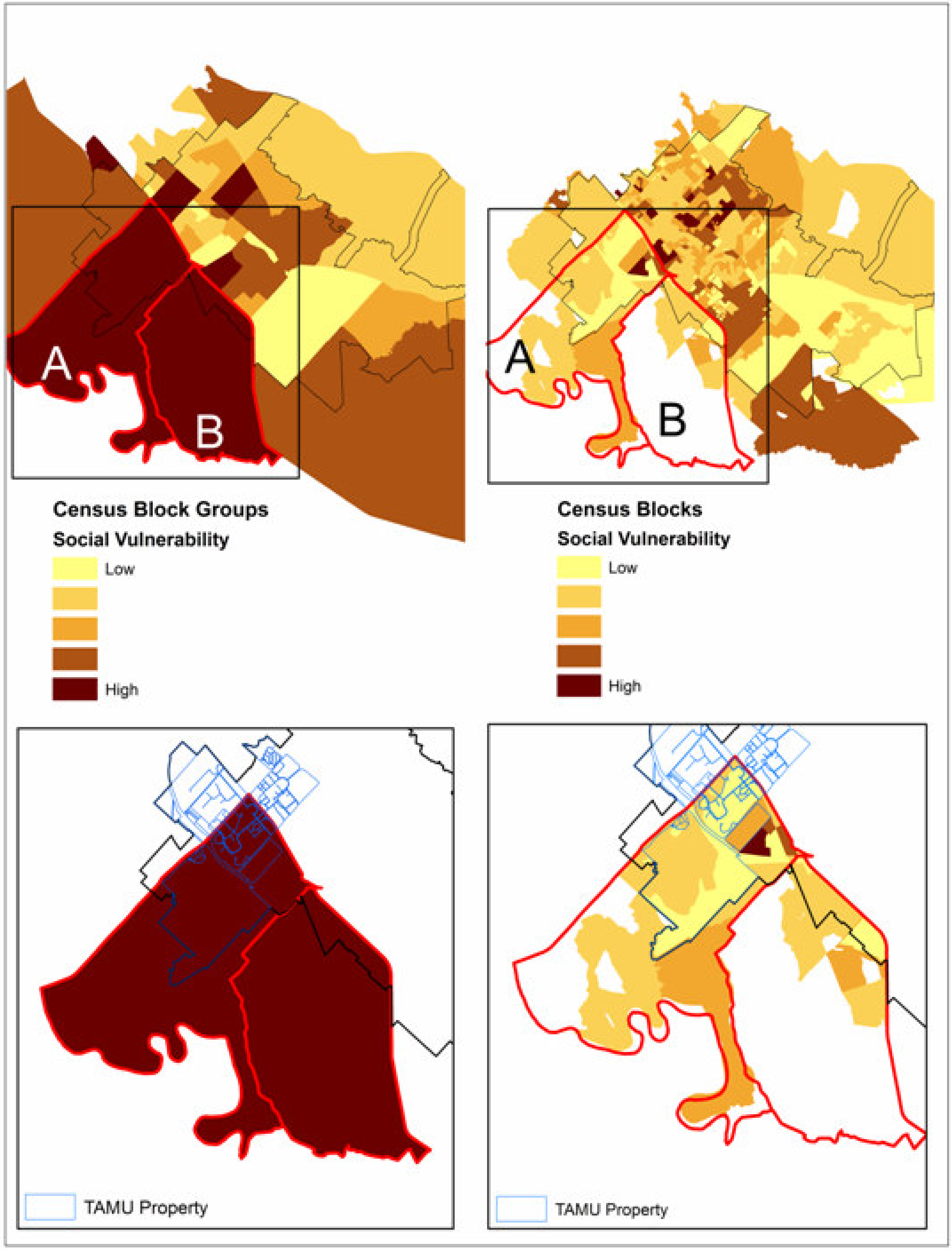

Figure 6. College Station CBG and CBLK Results

The CBGs are labeled A and B to distinguish between them. CBG A has high social vulnerability in College Station because of a high concentration of housing units, females, non-whites and a high total population. Because CBA A includes a portion of the Texas A&M University (TAMU) campus, it reflects the student population which, according to the overall SVI analysis, contains a large number of females and non-whites. This is typical for College Station as a whole.

CBG B also exhibits high social vulnerability. However, the reasons for the high SVI are very different than CBG A. CBG B has high social vulnerability because it contains a very high concentration of persons under 18, occupied households, and very low median housing values. CBG B, unlike A, does not intersect the boundary of the TAMU campus, which may help explain their demographic differences.

Conversely, CBLK maps of social vulnerability do not show high SVI levels in College Station. In fact, only one CBLK has a high SVI because of high numbers of housing units and occupied households added to moderate numbers of females and non-whites. This CBLK is composed of duplex and apartment housing, mainly occupied by TAMU students.

The most striking difference between the CBLK and CBG results is the extreme difference in social vulnerability values. In the CBGs, the overall SVI showed high social vulnerably over large areas. However, the CBLK maps only show small pockets of the lowest social vulnerability within each CBG. This is because the CBLK aggregation allows for a more sensitive and geographically exact measurement of social vulnerability. Both CBG A and B have large spatial aggregations for Brazos County.

They both extend from the county border while only including a small section within the College Station city limits. Some CBLKs intersect the College Station city limit and extend into the county, but the majority of the 79 CBLKs fall within the city limits.

Another major difference is the presence of the TAMU campus. The campus has a diverse population with a high population of females and non-whites. However, the TAMU campus is very large and has areas where there is no student housing. This is seen in Figure 6 where only the western part of the campus where there is no student housing, and containing agricultural land as well as the airport is included. CBLK aggregation better represents College Station's social vulnerability because it better identifies populated areas and captures variations in vulnerability that the CBG data cannot.

Hazard Results

The final test of CBLK superiority over CBG for measuring social vulnerability is to overlay the potential threat of a hazard, in this case a train derailment, on College Station's overall social vulnerability index to demonstrate CBLKs are better at identifying at-risk populations.

As stated earlier, College Station contains a stretch of the Union Pacific Railroad which is a source of concern because of the potentially high threat to the city and its residents compared to other hazards in the area. Brazos County and College Station emergency managers have designated a standard one-half mile evacuation areas. In the CBG results for College Station, 20 out of 47 CBGs intersect some part of the one-half mile evacuation area (Table 11). Table 12 shows the demographics of those CBGs within the evacuation limit. According to the computed results of the CBG social vulnerability test, over half of the entire College Station population lives in the area that intersects the emergency one-half mile buffer. That would mean that at any given time half of the entire population of College Station is potentially at risk from a train derailment.

Table 11. Demographics of CBG in the Train Derailment Evacuation Area

Demographics	Total	Mean	Min	Max
Total Population	44,226	2,211.30	778	9,742
Non-White	8,977	448.85	109	1,360
Female	21,278	1,063.90	246	4,471
Age Under 18	6,728	336.40	29	839
Age Over 65	1,636	81.80	1	206
Households	14,341	717.05	8	2,076
Housing Units	15,403	770.15	8	2,338
Median Housing Value		$92,260	$11,100	$165,900

Table 12. Demographics Differences within the CBG that Intersect the Evacuation Area

Demographics	CBG	College Station	Remaining Population
Total Population	44,226	67,890	23,664
Non-White	8,977	13,217	4,240
Female	21,278	33,223	11,945
Age Under 18	6,728	20378	13,650
Age Over 65	1,636	2,461	825
Households	14,341	24,691	10,350
Housing Units	15,403	26,054	10,651
Median Housing Value			

Conversely, the CBLK computed results provided a different analysis. Out of the 773 CBLKs along College Station, 225 intersect the one-half mile evacuation area. Table 13 lists the demographics of those CBLKs within the evacuation area. Compared to CBG aggregation the CBLK aggregation shows that less than half of the entire College Station population is at risk from train derailment (Table 14).

Table 13. Demographics of CBLK in the Train Derailment Evacuation Area

Demographics	Total	Mean	Min	Max
Total Population	25,689	113.67	0	4,448
Non-White	5,064	22.41	0	517
Female	12,008	53.13	0	1,609
Age Under 18	2,934	12.98	0	370
Age Over 65	625	2.77	0	128
Households	9,700	42.92	0	678
Housing Units	10,393	45.99	0	818
Median Housing Value		$99,007	$11,100	$165,900

Table 14. Demographics Differences within the CBLK that Intersect the Evacuation Area

Demographics	CBLK	College Station	Remaining Population
Total Population	25,689	67,890	42,201
Non-White	5,064	13,217	8,153
Female	12,008	33,223	21,215
Age Under 18	2,934	20378	17,444
Age Over 65	625	2,461	1,836
Households	9,700	24,691	14,991
Housing Units	10,393	26,054	15,661
Median Housing Value			

Figure 7, again illustrates the CBG aggregation masking meaningful variations in the SVI, resulting in the potential for including populations outside the College Station city limits thus creating a misleading picture of social vulnerability to the threat of a train derailment. Since CBLKs are small, they do not mask as many meaningful geographic variations as the CBGs.

If emergency officials were to follow the CBG map, they would mistakenly begin to evacuate populations over a large area in College Station. In the case of the CBG map, there is entirely too large an area for a timely evacuation. However, if emergency officials were to use the CBLK map, they could better recognize the small pockets of highly concentrated social vulnerability that are in need of special attention. The large areas covered by CBGs mask the few smaller areas of greatest concern within the train derailment evacuation area. Though there might be errors in the use of both, the CBLKs uncover patterns of social vulnerability in a way that CBG cannot. Therefore, CBLK data provide a more exact location and measurement of social vulnerability than CBG data.

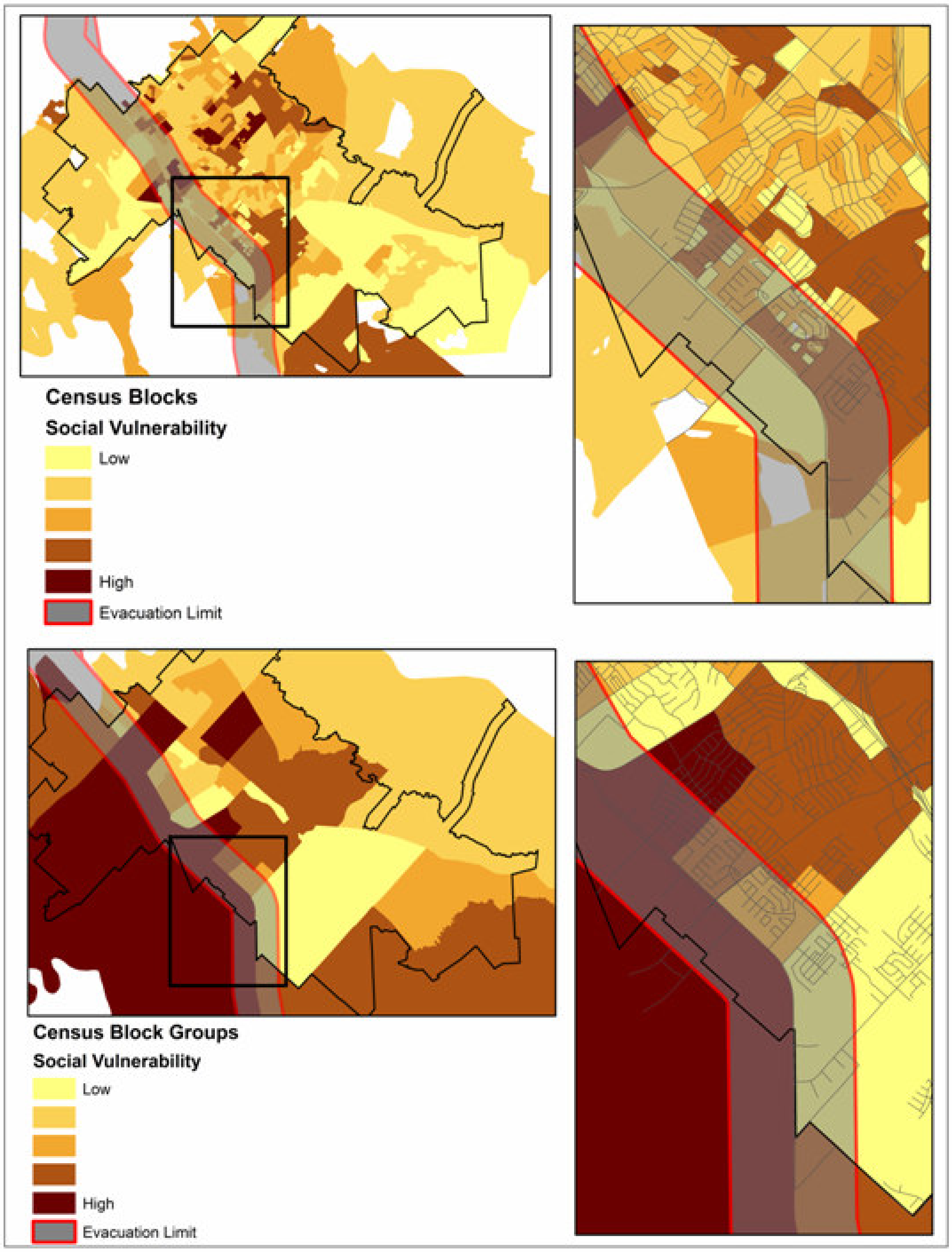

Figure 7. Overall Social Vulnerability in CBG and CBLK with the Evacuation Area

CHAPTER V

SOCIAL VULNERABILITY SUMMARY AND CONCLUSION

Social vulnerability was computed using CBGs and CBLKs at a county and municipal-wide scale. This was done to determine if CBLKs can provide more exact measurement of social vulnerability than CBGs. The countywide results were used to argue that CBLK provided a better representation of variability when computing social vulnerability and better displays a distinction between rural and urban social vulnerability, which CBGs could not do.

The municipal-wide results were used to argue that CBLKs could compute a more exact measurement of social vulnerability than CBGs for a municipality. It was shown that CBLKs enable a more exact measurement of social vulnerability. It was shown that within the CBGs with high concentrations of vulnerability, there exist CBLKs with lower levels of vulnerability.

Finally, the hazard overlay test using a potential train derailment, used College Station's overall social vulnerability to argue CBLKs are superior for showing the at-risk populations than CBGs. The results, again, show CBLKs better captured small pockets of high-risk areas because of geographic sensitivity to at-risk populations. By using the CBLK social vulnerability analysis, emergency officials can determine social vulnerability more precisely and not be affected by the zoneation effect of a MAUP and thus reducing the potential for introducing ecological fallacy into the analysis.

MAUP and ecological fallacy were shown to be reduced by using CBLKs because it was able to compute social vulnerability at an aggregation level low enough that meaningful geographic variations were not masked as when using CBGs.

This study sought to answer, “Is the use of census block data advantageous when analyzing social vulnerability at the city level?” This study has shown that there are advantages to using CBLKs in municipal social vulnerably analysis. First, because CBGs cover larger areas, they include populations that are in no way representative of the population in a municipal-wide analysis. CBLKS, on the other hand, because of their lower aggregation level, can be more sensitive and geographically exact in measuring social vulnerability than CBGs.

A second advantage of using CBLKs is their ability to cover as large an area as CBGs while providing a better and more sensitive computation of social vulnerability. It is possible to map the entire county at the CBLK level and make distinctions between the diverse populations in rural and urban areas. Using CBLK can reduce, though not eliminate, the danger of introducing problems with the ecological fallacy. This is especially important for emergency managers because when they see SVI maps they may believe vulnerability in a CBG and CBLK is homogenous among the population, when in fact it is not. The CBLKs allow them to better interpret the social vulnerability for smaller areas to understand spatial patterns of vulnerability at a finer spatial scale. Therefore, by using a map of social vulnerably at a higher resolution, they can better plan for emergencies.

Better planning from using CBLK analysis may reduce costs. By having a better idea where socially vulnerable populations are located, emergency and government officials can allocate funds to other more serious problem areas. Finally, having a more exact measurement of social vulnerability is beneficial for fulfilling the Robert T. Stafford Disaster Relief and Emergency Assistance Act which has recognized the need to conduct vulnerability studies to improve the distribution of aid.

Limitations

Social vulnerability in a municipal setting using census block level data can provide a better account of those populations who are more or less vulnerable to hazardous events. The Cutter, Mitchell, and Scott (1997) method for calculating social vulnerability has shown that it can be applied to census blocks and retain its objectivity as a vulnerability measurement. However, though their social vulnerability method is so far one of the more objective forms of measuring vulnerability, it is not without its faults. There are numerous data errors and other variables not taken into account when calculating social vulnerability. Their method uses US Census data which contains slight numerical errors to protect privacy rights. Some of the census data has been double counted. In the census blocks, the data for non-whites included Hispanic/Latinos. The census does not count Hispanic/Latino as a race, as they can be all races, but in the block calculations they are added to the race and population categories. To compensate, the census blocks subtracted the Hispanic/Latino count to get the correct population count.

The Cutter, Scott, and Mitchell (1997) social vulnerability method used some variables in their original that were not available from the US Census Bureau. Two in particular had to be changed or omitted. First was the average housing value. The US Census does not list the average housing value; rather they released the median housing value. This may change the social vulnerability outcome if an area has access to average housing values by census blocks. Second, they discussed the use of the census variable of mobile homes as one indicator of social vulnerability. Again, the US Census Bureau did not include mobile homes in any of their data sets. Finally, their use of housing value data are used as a proxy for income; since the census data includes income data, it may be better to use the direct measurement.

Though there are some slight errors in the social vulnerability calculation, its overall importance remains. Through the Cutter, Scott, Mitchell (1997) method of social vulnerability calculations, especially within a municipality, they have created a base standard of measurement. For a municipality such as College Station, future research using surveys can help determine the validity of the social vulnerability calculations. However, until then, the current method is the most cost effective and objective form of calculating social vulnerability to provide government decision makers a better perception of emergency planning needs.

In addition, the location of this study created its own limitations. College Station is unique in Brazos County because it contains Texas A&M University which covers an area of 21.04 sq km (5,200 acres) and houses a variety of multi-racial and international students. The demographics of the university change annually depending on enrollment. In addition to constant changes in student demographics, student's residency also fluctuates. Generally, the students of Texas A&M University make up a large portion of the College Station population (±45,000). The majority of students reside in and around College Station seasonally. During the school year, students are an integral part of the city of College Station. However, during winter and summer breaks (and other breaks) the majority of the students leave. These constant fluctuations in the demographics could possibly alter the outcome of social vulnerability calculations for College Station. Though the university sets its own development and care for its students, College Station still maintains a level of responsibility for aiding those vulnerable to hazards. This includes the students living around and on the university campus.

It is possible to remove the Texas A&M campus demographics from the College Station social vulnerability analysis. However, little difference was in the social vulnerability results, the only reason for removal would be the preference of the emergency manager. However, by removing the Texas A&M University property, an emergency manager could be perceived, by local citizens and students, as alienating a population that makes up a large portion of the city. This could cause problems because the campus, and College Station's economic livelihood, has the most to lose in a hazardous event such as a train derailment.

Future Research

This study examined one county for its analysis of CBLK and CBG social vulnerability mapping. More research needs to be conducted on other counties to determine if CBLK aggregation is superior to CBG in social vulnerability studies. This includes more social vulnerability studies at the county and the municipal scale. These studies will help enforce if the use of CBLK in social vulnerability studies and provide more analysis of the variability among the aggregated results. In future studies, the use of census data on income as a direct measure should be investigated. In addition, a method of removing areas not used for residential areas should be developed, and tested.

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